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RESEARCH ARTICLE

Development of an Adaptive AHP Path Planning Method Considering the Mobile Robot Driving Environment

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ABSTRACT This paper aims to enhance the Analytic Hierarchy Process (AHP)-based path planning algorithm by addressing some of its shortcomings. Existing algorithms both struggle to identify optimal paths and lack a systematic approach for constructing relative importance matrices (RMs). To remedy this, the proposed AAHP method integrates the A* algorithm to enhance path efficiency and incorporates robot sensor detection to systematically determine the optimal RM, unlike the existing AHP method. The performance of the proposed algorithm was evaluated by comparing the navigation performance of the existing AHP method, AAHP without A*, and AAHP in various scenarios. Simulation results demonstrate the AAHP's superiority over existing methods in terms of distance and rotation, ultimately highlighting its efficiency in path planning.

INDEX TERMS Mobile robot navigation, analytic hierarchy process, optimal path planning, relative importance matrix.

NOMENCLATURE

O_n	Value of objective that subscript (n) indicates n = {**distance**, **rotation**, **safety**, ...}
O_{norm}	Normalized value of objectives
O_{ldist}, O_{lang}, $O_{lsafety}$	Value of local objective for distance, rotation, and safety
W_m	Weight that subscript (m) indicates m = {**object**, **candidate**, ...}
W_{obj}, W_{cand}	Weight for each objective and candidates
W_{o1}, W_{o2}, W_{o3}	Weight for each objective
$W_{o1ortho}$, $W_{o2ortho}$	Weight of 2D projected objectives
W_{odist}, W_{orot}, $W_{osafety}$	Weight of each objectives
$X(x_i, y_i, \theta_i)$	X: **robot pose**, pose component that subscript (i) indicates i= {**A***, **cand**, **goal**, **robot**}
R_{avg}, R_{max}	Average measurement range of the LiDAR, Maximum range of the LiDAR

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I. INTRODUCTION

Autonomous driving technology is expected to be used in all areas of our lives with the ushering in of the era of the 4th Industrial Revolution [1], [2]. This innovative technology is currently going through the process of maturing within numerous production areas, such as self-driving cars as well as various services using mobile robots [3], [4]. The technologies required to implement autonomous driving include cognitive technology to obtain information about the surrounding environment using sensors; decision-making technology, including localization, map building, and navigation; and control technology that moves the robot along the planned path [3]. Navigation, which belongs to the field of decision-making technology and includes path planning, is the part that involves planning the robot's driving path, and it is being actively researched as one of the fundamental technologies in implementing autonomous driving [5].

Path planning algorithms include global path planning and local planning, and they are selected depending on the path planning scope and the scope of information used for path planning [6]. Global path planning is a method of finding the optimal path using information about the driving environment as a whole. This can find the optimal path from the starting position to the destination, but it is necessary to have accurate and sufficient information about the work environment to find the optimal path, and it also requires a lot of calculations [7]. This makes it difficult for global path planning to avoid dynamic obstacles such as moving people and changes in the environment.

A representative global path plan is the Dijkstra algorithm [8]. The Dijkstra algorithm was designed to find the two nodes with the shortest distance between them in a working space. By finding the shortest path by connecting all nodes in the environment, the Dijkstra algorithm has the advantage of always being able to find the optimal path, but it also has the disadvantage of requiring a large amount of calculation. To overcome this shortcoming, the A* algorithm was developed [9]. The A* algorithm is similar to the Dijkstra algorithm, but it does not compute paths to all nodes. Instead, the optimal path is calculated by introducing a heuristic estimate $h(x)$ to estimate the best path for each node. This has the advantage of reducing the calculation load, which is a disadvantage of the Dijkstra algorithm. However, if the user fails to properly set the heuristic estimate $h(x)$, it is possible that the optimal path will not be derived.

Meanwhile, the D* algorithm [10] was developed to improve the dynamic obstacle avoidance ability of the A* algorithm. To calculate a more natural path for the algorithm, the Field D* algorithm [11] and Theta* algorithm [12] were developed sequentially.

Another global path planning method is the sampling-based global path method. This approach randomly forms points to find the optimal sampling set; an algorithm of this type is the RRT algorithm [13]. The RRT algorithm creates nodes in random empty space until it reaches the destination, and it uses the set of nodes at that time. The RRT algorithm has proven its performance in the DARPA Urban Challenge [14]. However, the RRT algorithm suffers from disadvantages in that it does not guarantee an optimal path and that the generated path is not smooth. To solve these shortcomings of the RRT algorithm, the RRT* algorithm was proposed [15], [16]. The informed RRT* algorithm has also been proposed for faster calculation of RRT* [17]. Another random sampling algorithm is the Probabilistic Roadmap Method (PRM). The PRM algorithm creates nodes throughout the terrain, then finds the optimal set of nodes and uses a path based on that set [18]. Meanwhile, in contrast to global path planning, there is also local path planning, which uses information from the robot's surroundings to plan its path.

Unlike global path planning, local path planning repeatedly calculates short-distance paths in sections within the robot's sensing area to ultimately move to the final destination. Local path planning has the disadvantage of having a high possibility of not finding the optimal path because it plans paths based on limited environmental information. However, since it calculates the path for each short path, it can avoid dynamic obstacles.

A representative algorithm used for local path planning is the Dynamics Window Approach (DWA) algorithm [19]. The DWA algorithm is an algorithm that generates the path while considering the kinematic constraints of the robot and then selects the optimal path among the dynamic windows, which are valid paths that can move at linear speeds and angular speeds. When evaluating a dynamic window, an objective function is created by considering the distance from static obstacles, the distance to the target point, and the difference from the current speed, based on which the optimal solution is selected. The DWA algorithm is a widely used algorithm, but it suffers from the disadvantage of having to modify parameters appropriately.

The Vector Field Histogram (VFH) algorithm [20], which is another local path planning method, calculates different forward costs depending on the location of obstacles in each direction. The goal direction is determined by calculating the balance function according to the calculated forward cost. The VFH algorithm achieves advantages in real-time performance and accuracy. However, the VFH algorithm has a limitation that may make it inappropriate for actual application because it does not consider the dynamics and kinematics of the robot. The VFH+ algorithm has been proposed to overcome this limitation [21]. The VFH+ algorithm has been used in various studies because it solves existing shortcomings by determining the optimal movement direction by considering both the rotation speed and width of the robot [22], [23].

A widely used local path planning algorithm is Artificial Potential Field (APF) [24]. The APF algorithm is a method of finding the optimal movement direction by defining that an attractive force acts in the destination direction and a repulsive force acts in the obstacle direction. The APF algorithm shows good performance in real-time driving because it uses a simple mathematical model. However, the APF algorithm also suffers from disadvantages such as a local minimum in which the sum of repulsion and attraction becomes 0, as a result of which it cannot move and therefore does not reach its destination. Various algorithms have been presented in attempts to solve this problem, and they have yielded promising results. One such algorithm involves changing the repulsive potential function [25]. Another one involves setting up a virtual obstacle around the robot to draw a repulsive force [26].

The focus of the present study is on improving one of the local path planning algorithms, i.e., the Analytic Hierarchy Process (AHP)-based path planning algorithm. AHP is an evaluation technique that was designed by T. L. Saaty in the 1970s, and it can be used in multi-criteria decision-making that includes qualitative elements [27], [28]. AHP stratifies complex problems and performs quantitative pairwise comparisons of each factor to derive their importance and produce optimal results. Due to these advantages, it has been used in various situations, such as determining the location of power plant construction and the construction location of social facility infrastructure [29], [30]. It has also been used to determine rescue targets in disaster situations or improve line keeping systems [31], [32].

In AHP-based path planning, the locations where the robot can move are comprehensively and quantitatively evaluated against various factors while applying the user's preference to select the optimal location and repeating this process to calculate the path from the current location to the final destination [33]. The factors considered here are the distance to the destination, the angle at which to turn, and collision safety. Moreover, candidates for selection, i.e., the robot's moving position, were defined as points on the robot's lidar sensing boundary. The existing AHP-based path planning algorithm has shown results that can find an appropriate path. The advantage of AHP-based route planning is that it makes navigation possible while simultaneously considering various factors, and that the user's preferences can be reflected in each factor. For example, in tasks where a short driving distance is most important, the highest weight is given to the driving distance, which allows the robot to travel the shortest distance. Meanwhile, in cases where collision safety is most important, the greatest weight is given to the aspect of collision safety and AHP plans the safest route. This has been confirmed in previous works [33], [34], [35], [36]. However, in the AHP framework, it is necessary to define a pairwise comparison matrix between each criterion considered in the part that reflects the user's preference. However, the existing AHP suffers from a limitation in that it cannot not systematically design parts that reflect user preferences. The user has to arbitrarily define a pairwise comparison matrix between objectives, and there is also a problem wherein an appropriate path cannot be drawn if the pairwise comparison matrix between objectives is not defined appropriately for the environment. To solve this problem, the current study improved upon this existing algorithm to secure globality of AHP-based path planning, which is a local path planning method.

The local solution determined through the robot's local information was also reevaluated from a global perspective and designed to find the optimal path despite changes in the environment.

The rest of this paper is structured as follows. Section II explains the detailed application method and limitations of the existing AHP-based path planning method. Section III explains the details of the Adaptive Analytic Hierarchy Process (AAHP)-based path planning algorithm, which was designed to overcome the limitations of the existing AHP-based path planning algorithm. The results of a simulation applying the AAHP-based path planning algorithm are summarized in Section IV. Finally, Section V concludes the paper.

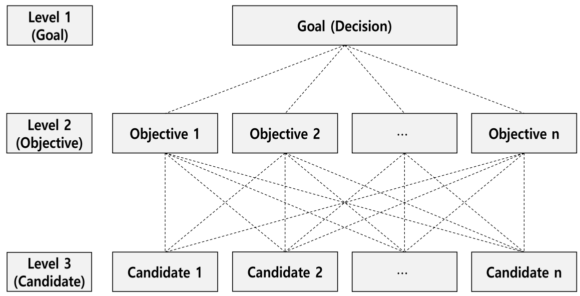

FIGURE 1. Structure of AHP.

II. PROBLEM DESCRIPTION

A. PRELIMINARY STUDY ON AHP-BASED PATH PLANNING

In many field applications involving the use of autonomous mobile robots (AMR), path planning is a very important factor in improving productivity. In this context, changes in the work environment, such as the appearance of other workers or obstacles that were not previously defined, increase the need for dynamic environmental response capabilities in mobile robot-based services. For example, in a smart factory, workers, obstacles, or other robots may frequently appear in the path of the moving robot. To respond to such situations, efficient path planning and modification of the path plan based on local sensor information are essential. Accordingly, the current study proposes a route planning algorithm that integrates global route planning and local route planning methods.

AHP is a multi-objective decision-making method that finds the optimal solution (goal) among multiple candidates by simultaneously considering multiple factors (objectives). Figure 1 depicts the decision-making structure of AHP.

Various studies have been conducted to plan the path of a mobile robot while reflecting these characteristics of AHP [34], [35], [36]. In AHP-based path planning, among the points on the sensing boundary measured through the robot's sensors, points where the robot can move are defined as candidates. Each defined candidate is evaluated based on the distance from the point to the destination (O_{dist}), the angle between the robot and the point (O_{ang}), and the safety when moving to the point (O_{safety}).

In AHP-based decision making, the optimal solution is determined based on the relative importance (RM) matrix between objectives. This RM is defined as equation (1) according to the decision-maker's specific preferences and priorities.

$$RM = \begin{bmatrix} O_1/O_1 & O_1/O_2 & O_1/O_3 \\ O_2/O_1 & O_2/O_2 & O_2/O_3 \\ O_3/O_1 & O_3/O_2 & O_3/O_3 \end{bmatrix} = \begin{bmatrix} 1 & a & b \\ 1/a & 1 & c \\ 1/b & 1/c & 1 \end{bmatrix}, \quad (1)$$

where O_1, O_2, and O_3 represent the 1^{st}, 2^{nd}, and 3^{rd} objectives, respectively. AHP uses integers from 1 to 9 to define relative importance. Once RM is determined according to the user's preference, it is normalized as shown in equation (2) to obtain a weighted objective matrix.

$$O_{norm} = \left[\frac{O_{i1}}{\sum_{i=1}^{n} O_{i1}}, \frac{O_{i2}}{\sum_{i=1}^{n} O_{i2}}, \cdots, \frac{O_{in}}{\sum_{i=1}^{n} O_{in}} \right], \quad (2)$$

where i=1, 2, $\cdots$, n, and n is the number of objectives. By calculating the average of each column in equation (2), the following weighted objective matrix can be obtained. The focus of this study is on improving one of the local path planning algorithms, i.e., the Analytic Hierarchy Process.

$$W_{obj} = \left[\frac{\sum_{j=1}^{n} O_{norm(1,j)}}{n}, \frac{\sum_{j=1}^{n} O_{norm(1,j)}}{n}, \ldots, \frac{\sum_{j=1}^{n} O_{norm(1,j))}}{n} \right], \quad (3)$$

where W_{obj} is a $1 \times$ n row matrix. Finally, W_{obj} refers to the weight of each objective that is considered in the decision-making process. The next procedure is to evaluate what value all candidates have for the considered objective. Equation (4) evaluates the value of a candidate through the ratio of the value of each candidate to the $i-th$ objective.

$$E(O_i)_{lm} = \frac{O_i(C_l)}{O_i(C_m)}, \quad (4)$$

where l and m represent the l^{th} and m^{th} candidates. Once the evaluation matrix for each objective is obtained, weighted candidate matrices are obtained through the same procedure used in equations (2)-(3). First, the normalized form of equation (4) is defined as follows.

$$E(O_i)_{norm} = \left[\frac{E(O_i)_{l1}}{\sum_{l=1}^{\gamma} E(O_i)_{l1}}, \frac{E(O_i)_{l2}}{\sum_{l=1}^{\gamma} E(O_i)_{l2}}, \cdots, \frac{E(O_i)_{l\gamma}}{\sum_{l=1}^{\gamma} E(O_i)_{l\gamma}} \right]. \quad (5)$$

The weighted candidate matrix for each objective can be found as follows

$$W_{cand}(O_i) = \left[\frac{\sum_{m=1}^{\gamma} E(O_i)_{norm(1m)}}{\gamma}, \frac{\sum_{m=1}^{\gamma} E(O_i)_{norm(2m)}}{\gamma}, \cdots, \frac{\sum_{m=1}^{\gamma} E(O_i)_{norm(\gamma m)}}{\gamma} \right]. \quad (6)$$

All the functions are then considered to obtain the following weighted candidate matrix:

$$W_{cand} = \left[W_{cand}(O_1)^T, W_{cand}(O_2)^T, \cdots, W_{cand}(O_n)^T \right]. \quad (7)$$

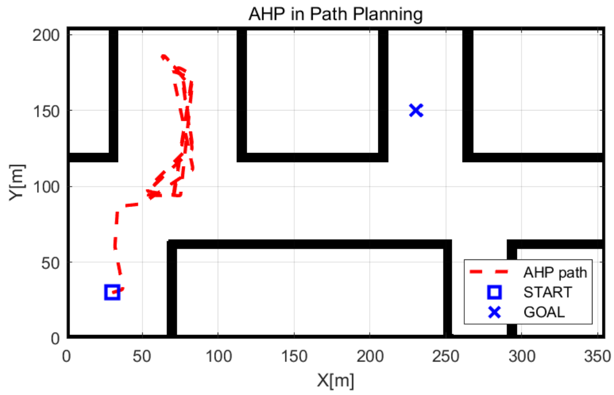

FIGURE 2. AHP-based path planning with an inappropriate RM.

This process allowed for the weight for each objective to be determined, and the final selection was made according to the following equation.

$$Function^* = \arg\max(W_{cand} \times W_{obj}^T), \quad (8)$$

where W_{cand} is a $k \times l$ matrix, where k is the number of objectives and l is the number of candidates. Meanwhile, W_{obj}^T is a weighted objective vector. In AHP-based path planning, as the robot moves to its destination, the next location that it will move to is determined from the robot's current location based on an AHP-based decision-making method; this process is repeated until the robot reaches its final goal.

B. LIMITATIONS AND CORRESPONDING IMPROVEMENTS OF AHP-BASED PATH PLANNING

As explained earlier, AHP is a method of deriving optimal results by reflecting the user's preferences for various criteria under consideration. However, there is no systematic way to determine which RM is most appropriate in a specific environment. Therefore, relative importance was set based on the user's arbitrary preference, and the same RM was applied to all sections of the robot's driving. However, this method fails to reflect changes in the work environment, and if an appropriate RM is not set, an inappropriate path is created, as shown in Figure 2; this is an example of a robot failing to reach its destination because it is making infinitely repeated movements in a specific area due to an incorrectly defined RM. In other words, the existing AHP has the disadvantage of not being able to reflect the robot's work environment. It is therefore necessary to use an algorithm that generates an RM suitable for the environmental situation in which the robot is located.

Moreover, the existing AHP-based path planning algorithm is a local path planning method that uses only the robot's sensing information. Because local path planning plans the robot's path based on environmental sensor information that is acquired as the robot moves, it is possible that the robot may fall into a local minima situation or create an inefficient path. Therefore, in this study, we propose Adaptive AHP-based path planning, which is an AHP-based path planning that

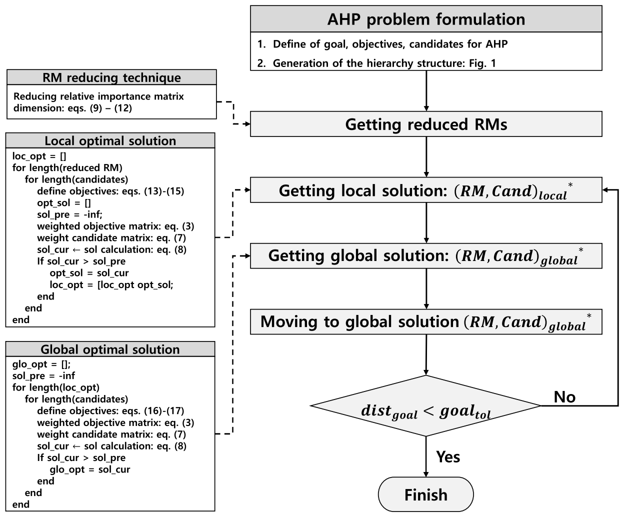

FIGURE 3. Adaptive AHP algorithm.

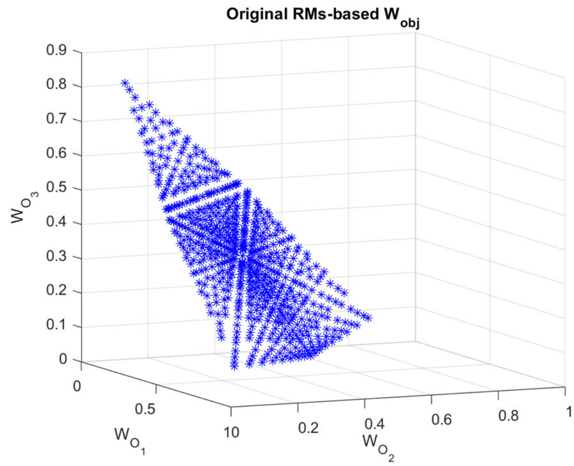

FIGURE 4. Original RMs in $W_{o1}W_{o2}W_{o3}$ space.

improves upon the limitations of the existing AHP-based path planning.

In summary, the limitations of existing AHP-based path planning are, first, that there is no systematic method with which to suggest the optimal RM for the various driving environment, and secondly, as a limitation of the local path planning method, the optimality of the planned path cannot be guaranteed.

Therefore, the main contributions of the AAHP proposed in this study are as follows: It analyzes the robot's driving environment and proposes a method to derive RM that can make optimal decision in each situation. Further, to overcome the limitations of local route planning, the A* algorithm, which is a global path planning method, was included in the AHP-based decision-making process.

III. METHODOLOGY

In this section, we elaborate upon the proposed path planning algorithm. The structure of the proposed AAHP is shown in Figure 3. The proposed algorithm follows the procedure presented in Figure 3. The implementation of sub-functions such as RM reduction technique, getting local solution, and getting global solution are also explained in detail through pseudo code. Considering all RMs defined in the AHP framework would reduce computational efficiency, so the reduced RM is obtained first. Next, candidates are defined through external environmental information measured by the robot's sensors.

Then, candidates based on local sensor data are evaluated based on the reduced RM set and the considered objectives, after which a final optimal solution set $(RM, Cand)^*_{local} = \left\{\left(RM_1, Cand^*_{RM_1}\right), \left(RM_2, Cand^*_{RM_2}\right), \cdots, \left(RM_i, Cand^*_{RM_i}\right)\right\}$ is obtained.

The final optimal solution, $(RM, Cand)^*_{global}$, is obtained using $(RM, Cand)^*_{local}$ and global information-based objectives.

The process of moving the robot to the derived solution position is repeated until the final destination is reached.

A. RELATIVE IMPORTANCE MATRICES

As the robot moves from its current location to its final destination, it is placed in various environments. The most intuitive way to find an RM appropriate for each environment is to apply AHP to all RMs that can be created. However, this method is not appropriate because it requires huge amounts of computations. Therefore, this study proposes a method to reduce the set of RMs that can be created.

RM is defined by forming a pairwise comparison matrix using an integer relative comparison scale ranging from 1 to 9. Based on the AHP decision-making process, W_{obj}, a weighted objective vector, is finally calculated as shown in equation (3).

Ultimately, W_{obj} refers to the weight for each objective being considered. In this study, three objectives are considered for route planning, so a total of 9^3 RMs must be considered. In fact, excluding matrices with the same ratio, $637 W_{obj} = (W_{o1}, W_{o2}, W_{o3})$ are expressed in $W_{o1}W_{o2}W_{o3}$ space, as shown in Figure 4, and the sum of each component can be expressed as follows:

$$W_{o1} + W_{o2} + W_{o3} = 1. \tag{9}$$

Figure 4 is a schematic representation of Equation 9. Because three objectives are considered for path planning of a mobile robot, they are expressed in the form of a 3D graph. The coordinates of each point represent the weight for the objective being considered.

However, considering 637 weights results in decreased calculation efficiency, so if equation (9) is projected onto the $W_{O1_{ortho}}W_{O2_{ortho}}$ plane using equations (10)-(11),

$$W_{O1_{ortho}} = W_{O_1}\cos\theta, \tag{10}$$

$$W_{O2_{ortho}} = W_{O_2}\cos\theta, \tag{11}$$

then we can get the following relationship

$$W_{O1_{ortho}} + W_{O2_{ortho}} \le 1, \tag{12}$$

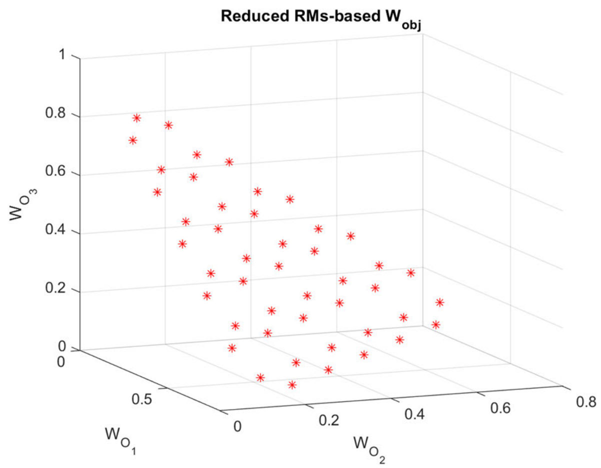

FIGURE 5. Reduced RMs in $W_{o1}W_{o2}W_{o3}$ space.

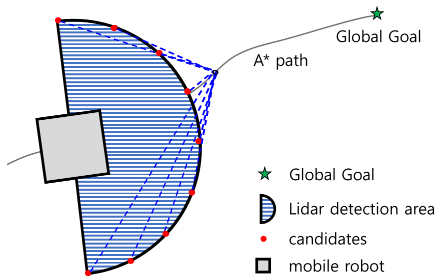

FIGURE 6. AHP decision making for local optimal solution.

where $\theta = 45°$, and $W_{O_{1ortho}}$, $W_{O_{2ortho}} > 0$. That is, for each RM, each W_{obj} is projected onto the area within equation (12) on the $W_{O_{1ortho}}W_{O_{2ortho}}$ plane. This area is divided into 0.1 intervals, the weights included in each area are designated as the median of the area, and the final 46 weight pairs $\left(W_{O_{1ortho}}, W_{O_{2ortho}}\right)$ are obtained. Finally, equations (9)-(10) are used to obtain two weight pairs (W_{O1} , W_{O2}) in the $W_{o1}W_{o2}W_{o3}$ space are obtained, while equation (8) is used to obtain W_{O3}. Figure 5 shows W_{obj} with the final reduced RM applied. To verify the effectiveness of the proposed RM reduce technique, a decision was made regarding the case of applying and not applying the RM reduce technique in an environment simulating a smart factory, which is the most complex case among the simulation scenarios tested in Section IV of this paper. The average time required was calculated. When the RM reduce technique was not used, the calculation time at each decision-making step was 1021 *ms*, and when the RM reduce technique was applied, the time required was 21 *ms*. These results confirm the effectiveness of the proposed RM reduce technique.

B. LOCAL OPTIMAL SOLUTION

After obtaining W_{obj} to which the reduced RM is applied, each candidate is evaluated through objectives based on local information to obtain the optimal solution set $(RM, Cand)^*_{local} = \left\{\left(RM_1, Cand^*_{RM_1}\right), \left(RM_2, Cand^*_{RM_2}\right), \cdots, \left(RM_i, Cand^*_{RM_i}\right)\right\}$ for each RM. Figure 6 shows the area detected by the mobile robot's lidar, candidates on the detection boundary, and the A* path.

To find the local optimal solution, it is necessary to evaluate each candidate, and the objectives for this are the distance between the A* path and the candidate ($O_{l_{dist}}$), the rotation angle to face the candidate in the robot's current orientation ($O_{l_{ang}}$), and the collision risk ($O_{l_{safety}}$) based on the distance to the obstacle, which is defined as follows.

$$O_{l_{dist}} = \sqrt{(y_{A*} - y_{cand})^2 + (x_{A*} - x_{cand})^2}, \tag{13}$$

$$O_{l_{ang}} = \left|\theta_{cand} - \theta_{robot}\right|, \tag{14}$$

$$O_{l_{safety}} = \begin{cases} 0, & (dist_{obs} \le r) \\ \dfrac{3}{r\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{3(x-2r)}{r}\right)^2}, & (r < dist_{obs} \le 2r) \\ 100, & (dist_{obs} > 2r) \end{cases} \tag{15}$$

where $dist_{obs}$ is the distance between candidate and obstacle, r is the radius of the mobile robot.

The robot considered in this study can detect in the forward direction through a lidar sensor. Points on the lidar sensing boundary were divided into equal intervals and defined as candidates among which the robot could move. For the 46 reduced RMs, a set of 46 pairs of local solutions that satisfy equation (8) is obtained by evaluating the objective defined in equations (13)-(15) among all candidates.

$$(RM, Cand)^*_{local} = \left\{\left(RM_1, Cand^*_{RM_1}\right), \left(RM_2, Cand^*_{RM_2}\right), \cdots, \left(RM_{46}, Cand^*_{RM_{46}}\right)\right\}.$$

In particular, the optimality of the local information-based solution was secured by considering A*, the global optimal path generation algorithm, and the distance to candidates.

C. GLOBAL OPTIMAL SOLUTION

Forty-six local optimal solutions were obtained through local environmental information obtained through the robot's sensors. In other words, in the process of finding the local optimal solution, each of the 46 reduced RMs derives a corresponding optimal solution. Note that there may be overlapping optimal solutions among the 46 RMs. Figure 7 depicts the situation of searching for the global optimal solution. As depicted in Figure 3, the AAHP framework uses the AHP framework to optimize the planned path, and it evaluates up to 46 candidates according to the global objective given below.

$O_{g_{dist}}$ represents the distance between each candidate and the goal position, $O_{g_{ang}}$ represents the rotation angle required for the robot to face the candidate, and $O_{g_{safety}}$ represents the obstacle density within the detection area when the robot moves to a specific candidate:

$$O_{g\_dist} = \sqrt{\left(y_{goal} - y_{cand}\right)^2 + \left(x_{goal} - x_{cand}\right)^2}, \tag{16}$$

$$O_{g\_ang} = \left|\theta_{cand} - \theta_{robot}\right|, \tag{17}$$

$$O_{g\_safety} = \frac{R_{avg}}{R_{max}}, \tag{18}$$

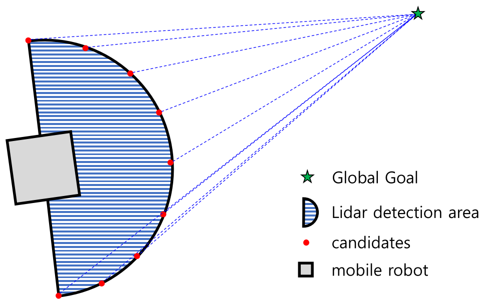

FIGURE 7. AHP decision making for global optimal solution.

where R_{avg} is the free space with in lidar detection area and R_{max} is the total lidar detection area. Once the final solution is determined according to equation (8), the robot moves to the corresponding location using motion control, and the same trial is repeated until the robot reaches the final destination.

IV. SIMULATIONS AND RESULTS

To demonstrate the performance of AAHP, MATLAB simulations were conducted in robot driving environments of various complexity. The characteristics of AAHP are that it is a method that can be used to suggest an RM that is suitable for the driving environment without using a uniform RM, and that it secures the optimality of the route by simultaneously considering the A* path, which is a global path planning algorithm. Two types of simulation scenarios were designed depending on the number of obstacles, and one type was designed in a smart factory environment. In the simulation, it was compared with the existing AHP and APF as local route planning methods. Additionally, the effect of including A* path planning in the proposed path planning algorithm was compared. Lastly, the superiority of AAHP was shown through comparison between the integrated version of APF and A* and AAHP (A* integrated version) proposed in this study. Further, in the scenario where the existing AHP was applied, changes in the path were confirmed by applying different RMs to the three objectives. Typically, the shortest distance driven and the small average rotation of the robot are used as measures of superiority in navigation performance. Therefore, to compare the performance of each method, the distance traveled by the mobile robot to reach the destination and the average rotation amount of the robot were investigated. For all simulation scenarios, it was assumed that the robot was given a mission to move across obstacles from the bottom left to the top right.

A. SCENARIO 1: FOUR OBSTACLES

The first simulation is a scenario in which a mobile robot moves to a destination within an environment in which there are four obstacles.

To apply the existing AHP, the following three cases were considered: $W_{obj} = \left(W_{o dist}, W_{o rot}, W_{o safety}\right)$ to $W_{obj_1} = (0.2,\ 0.2,\ 0.6)$, $W_{obj_2} = (0.2,\ 0.6,\ 0.2)$, $W_{obj_3} = (0.6,\ 0.2,\ 0.2)$. For each W_{obj}, different weights were applied to each objective in the mobile robot's navigation, and AHP was applied to examine the differences in navigation performance. Figure 8 shows the simulation results for different W_{obj} based on the existing AHP and APF. An interesting aspect of the APF results is that, although similar paths are planned as shown in Figure 8, the oscillations that occur during movement result in a greater final travel distance and average rotation amount of the robot. This highlights a weakness of the APF.

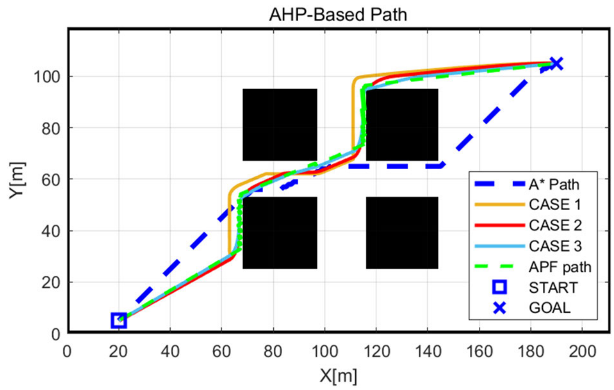

FIGURE 8. Navigation performance: conventional AHP-based path planning.

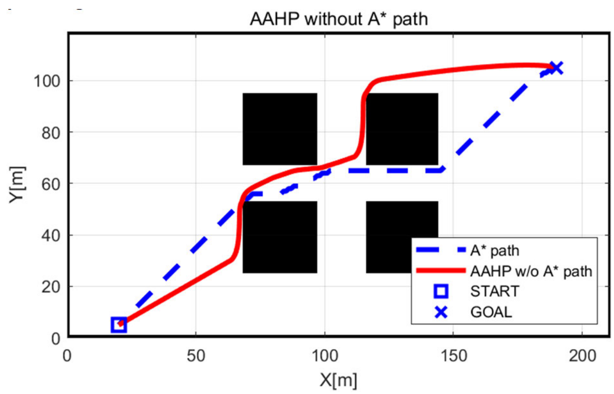

FIGURE 9. Navigation performance: AAHP without A* consideration-based path planning.

Figure 9 shows the navigation performance when using AAHP but not considering the global path, while Figure 10 shows the performance of AAHP while considering A* comparing APF with A*. From the simulation results, it can be seen that each method takes a different path.

The evaluation criteria were defined as the distance the robot needs to travel to reach its destination and the performance of maintaining the robot's straight motion.

The driving performance was confirmed by calculating the average value of the robot's driving distance and the total rotation for each simulation case. Table 1 lists the simulation results based on the existing AHP, APF and the proposed AAHP. Because the location where the robot moves through AHP is one of the points on the robot's sensing boundary, it moves the same distance every step. Therefore, the robot's

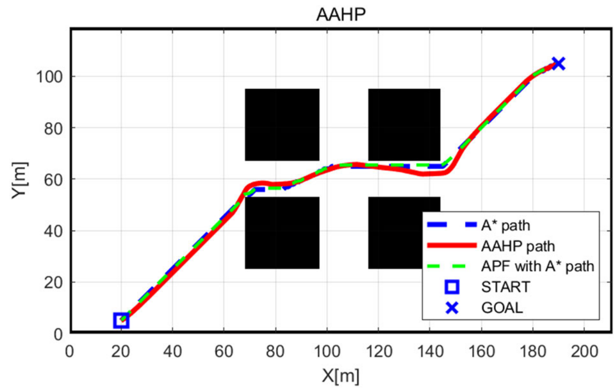

FIGURE 10. Navigation performance: AAHP-based path planning.

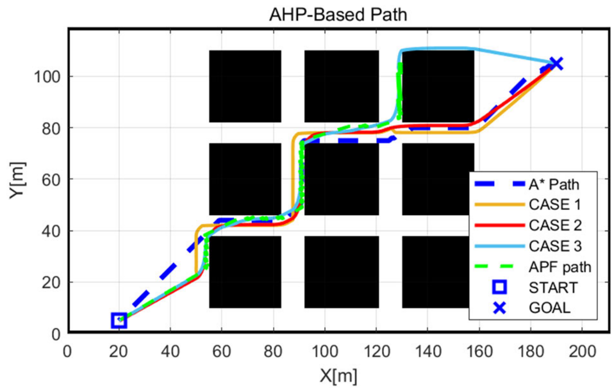

FIGURE 11. Navigation performance: Conventional AHP-based path planning.

TABLE 1. Simulation results of 4 obstacle scenario.

Method	Distance (m)	Δangle per step (rad)	Average Safety
AHP with W_{obj_1}	235.06	0.0061	0.9999
AHP with W_{obj_2}	224.71	0.0055	0.9210
AHP with W_{obj_3}	220.79	0.0124	0.9100
APF	437.20	1.6086	0.6231
A* Path	211.99	-	-
APF with A*	210.40	0.0318	0.7589
AAHP without A*	225.03	0.0063	0.9719
AAHP	212.79	0.0061	0.9854

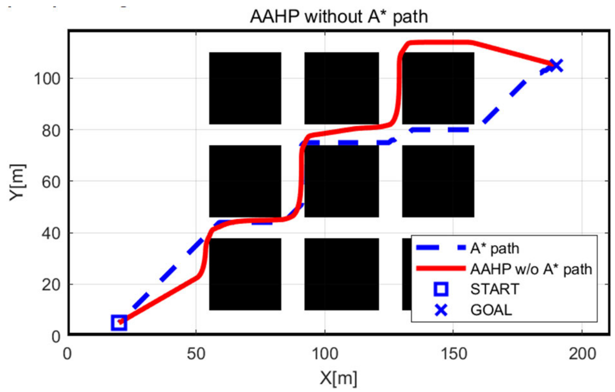

FIGURE 12. Navigation performance: AAHP without A* consideration-based path planning.

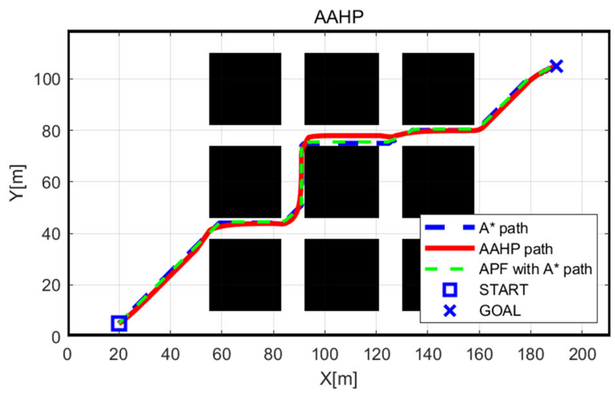

FIGURE 13. Navigation performance: AAHP-based path planning.

moving distance is proportional to the number of steps the robot moves to reach the destination.

First, when examine the existing AHP results, it was confirmed that the simulation results of W_{obj_3}, which placed the greatest weight on the moving distance, showed the shortest distance, while W_{obj_2}, which placed the greatest weight on the robot's ability to go straight, showed the minimum average rotation. It was confirmed that the navigation characteristics were displayed well. In the APF scenario, oscillation, which is the limit of the potential field, was discovered, and it was confirmed that unnecessary paths were calculated or rotated due to this. Additionally, it should be noted that, as expected, it was confirmed that the APF algorithm, designed to follow the A* path, calculates an improved path in terms of traveling distance, the average rotation of the robot, and improved safety compared to the original APF. In the AAHP-based navigation results, it can be seen that it successfully allows the robot to move the shortest distance, and in terms of the robot's straightness, it shows similar performance to W_{obj_2}, which places the greatest weight on the robot's rotation.

B. SCENARIO 2: NINE OBSTACLES

The second scenario is when a mobile robot moves to its destination in an environment with nine obstacles. The performance of the proposed algorithm was evaluated when the complexity of the environment increased compared to the first case. Figures 11 shows the navigation results of existing AHP and APF. Figure 11 shows the limitation of local path planning especially the artificial potential field method. Figure 12 displays the importance of A* to improve the path planning performance. Figure 13, finally, shows the superiority of AAHP comparing with AAHP without A*, APF with A*, and AAHP. The quantitative performance of the simulated methods is summarized in Table 2.

TABLE 2. Simulation results of 9 obstacle scenario.

Method	Distance (m)	Δ angle per step (rad)	Average Safety
AHP with W_{obj_1}	235.99	0.0083	0.9759
AHP with W_{obj_2}	223.90	0.0070	0.8778
AHP with W_{obj_3}	236.76	0.0127	0.8290
APF	Fail	Fail	Fail
A* Path	224.83	-	-
APF with A*	236.8	0.2140	0.5462
AAHP without A*	243.48	0.0087	0.8591
AAHP	222.78	0.0080	0.9158

FIGURE 14. Hyundai smart factory.

The simulation results in the second scenario showed excellent performance in both aspects of securing the shortest distance and straightness, showing similar trends to the first scenario, thus demonstrating the superiority of the proposed AAHP algorithm. The results of simulations of the first and second scenarios confirm that the proposed algorithm derives the optimal solution by reflecting the driving environment.

C. SITUATION 3: FACTORY-BASED MAP

A scenario was assumed to plan the path of a logistics robot operating in a smart factory environment [37]. As shown in Figure 14, the same simulation was performed in a scenario where production materials were transported between racks. We tested the proposed algorithm in a factory environment, which is a simplified production environment shown in Figure 14. Figures 15-17 show the simulation results obtained in this factory scenario.

By comparing the quantitative results presented in Table 3, the performance of the proposed algorithm showed that, among the existing AHP methods, the case that placed the greatest weight on distance actually moved the shortest distance, but it did not show superior performance in other cases. However, it was confirmed that the navigation based on the proposed AAHP algorithm generally provided excellent performance in terms of moving distance and rotation amount.

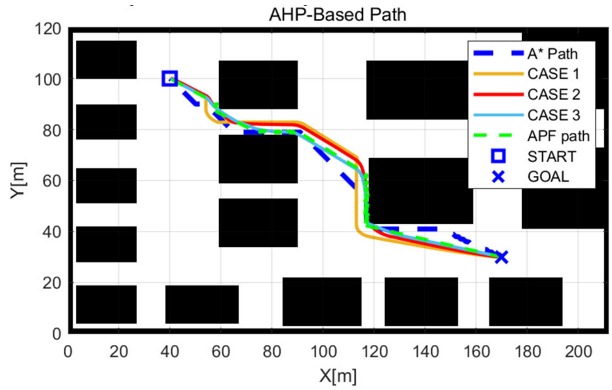

FIGURE 15. Navigation performance: Conventional AHP-based path planning.

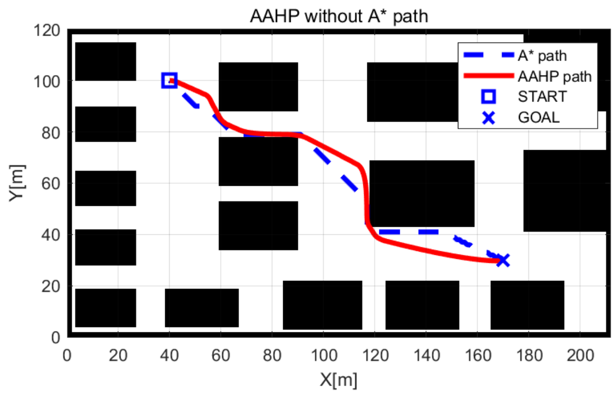

FIGURE 16. Navigation performance: AAHP without A* consideration-based path planning.

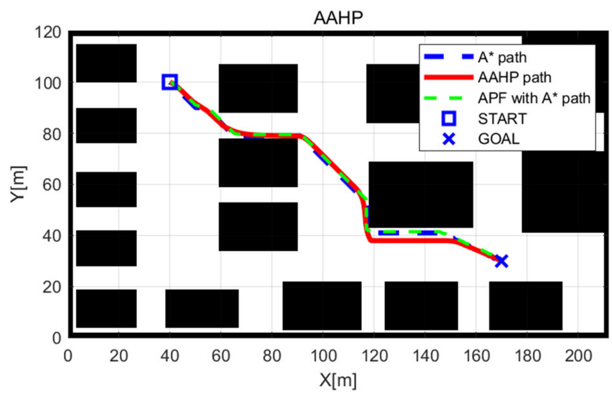

FIGURE 17. Navigation performance: AAHP-based path planning.

D. SUMMARY OF RESULTS

Through simulations, we aimed to demonstrate the superiority of the proposed algorithm by comparing it with existing path planning methods. To this end, we compared the well-known local path planning method APF and the traditional AHP-based path planning. Additionally, we validated the superiority of our proposed method by comparing the APF with A* and AAHP.

TABLE 3. Simulation results of a smart factory scenario.

Method	Distance (m)	Δ angle per step (rad)	Average Safety
AHP with W_{obj_1}	172.96	0.0082	0.9998
AHP with W_{obj_2}	163.19	0.0068	0.9342
AHP with W_{obj_3}	159.13	0.0069	0.8972
APF	261.4	1.2508	0.6064
A* Path	165.21	-	-
APF with A*	170	0.1542	0.6179
AAHP without A*	164.57	0.0072	0.8996
AAHP	162.59	0.0009	0.9287

To compare the performance of AAHP, simulations were performed for the existing AHP while applying a different relative importance matrix, the case where A* was not applied in AAHP, APF with A*, and the proposed AAHP. The existing AHP path plan defined different simulation scenarios with varying weights applied as CASE 1, CASE 2, and CASE 3. CASE 1 placed the highest weight on safety and, as expected, calculated a driving path away from each obstacle. CASE 2 gave the highest weight to rotation of the robot, and the results showed that the average angle change was actually relatively low. CASE 3 set the highest weight for distance. Accordingly, it was confirmed that the distance traveled tended to be the shortest as the weight for distance was the highest. However, in Simulation 2, contrary to expectations, CASE 3 was observed to travel a longer distance than CASE 1 and CASE 2. This can be said to be an example that exposes the limitations of local path planning, which shows that even when the greatest weight is placed on travel distance in AHP, the shortest path travel is not guaranteed. To improve this, AAHP utilized A* for path planning. To check the performance of AAHP, a simulation comparing it with the AAHP without A* algorithm was also performed simultaneously. As can be seen in Table 2, it was confirmed that there is a limit to achieving the shortest distance performance when neglecting to consider the path of the A* algorithm.

The A* algorithm is a global path planning method that calculates the shortest distance from the starting point to the goal and ensures the optimality of the planned path. The AAHP algorithm proposed in this study was designed to follow the A* algorithm to compensate for the inability to guarantee optimality of the route, which is a limitation of AHP-based route planning, one of the existing local path planning methods. However, due to the decision-making nature of AHP, there is no guarantee that the shortest distance will be calculated because multiple factors are considered simultaneously. Nevertheless, as can be seen in Tables 1, 2, and 3, the AAHP algorithm shows good performance not only for the driving distance but also for the angle change. Referring to Table 2, AAHP's results do not always provide the best results, but when considering overall aspects, AAHP's excellent performance could be confirmed.

V. CONCLUSION

This study improved upon the existing AHP-based path planning algorithm. There are certain disadvantages to the existing AHP-based path planning. One is that it is difficult to find the optimal path because it is a local path planning algorithm. The other is that, when applying AHP, there is no systematic method to set RM suitable for the robot's driving environment. When performing AHP-based path planning, the first weakness was overcome by considering the optimal path planning algorithm, A* path, and reevaluating the optimal point that was calculated using local information around the robot from the perspective of the entire terrain. The second weakness was solved by suggesting a method for proposing optimal RM while considering the driving environment. Based on the simulation results, it was confirmed that the suggested AAHP-based path planning showed overall superior performance and optimal driving performance compared to the existing AHP-based path planning. This study conducted simulations, and the results were able to determine the applicability of the proposed algorithm. In future research, we plan to conduct studies aiming to confirm the effect of improving navigation performance in driving environments of various complexity through actual robot hardware.

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